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From Ecological Modeling to Decentralized Optimization of Smart Power Grids

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Abstract: In this contribution we want to sum up how computer science, ecological modeling and control of distributed power systems mutually influence. First we show, how ecological modeling has been influenced by the availability of faster computers and easier to use programming environments. Then we argue that adaption and emergent behavior in biological systems observed e.g. at the hand of microscopic models can be interpreted as an optimization process. This observation led to new optimization (meta-)heuristics in computer science and inspired multi-agent based optimization and control methods. We motivate why these methods are an interesting choice for finding new solutions to planning and control problems in future electrical power systems. As an example we sketch a completely distributed, agent-based planning and control system for a so-called dynamic virtual power plant. Finally we discuss some directions of future research in the domain of agent-based control of distributed systems.

Keywords: Ecological Modeling, Nature-inspired Heuristics, Multi-agent Systems, Electrical Power Systems

1 Introduction and Overview

For several years now, 'swarm intelligence' and 'nature-inspired heuristics' are considered to be a promising approach for optimizing large distributed systems. This is particularly the case for optimization problems in the electrical power system (see e.g. [Mc07, AEH09, Ka14]).

In this contribution we want to sum up how computer science, ecological modeling and control of distributed power systems mutually influence. First we give a short introduction into ecological modeling and show, how this discipline has been influenced by the availability of faster computers and easier to use programming environments: particularly these conditions allowed the creation of microscopic population models. Then we argue that adaption and emergent behavior in biological systems observed, e.g. at the hand of microscopic models, can be interpreted as an optimization process. This observation led to new optimization (meta-)heuristics in computer science.

Currently our electrical power supply system is redesigned from a few large coal-fired or nuclear power plants to a large set of relatively small distributed power plants based on re-

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newable energy. But power generation from photovoltaic and wind power plants is volatile and does not necessarily correlate spatially and temporally to the demand. This and other reasons cause a substantial increase of complexity in controlling these distributed units to guarantee grid stability and reliability of supply. After a very brief introduction into current challenges of our power system in section 4 we motivate why optimization heuristics and artificial intelligence methods are an interesting choice for finding new solutions to control problems in this context. In section 4.2 we show the enormous increase of research in this area in the last 10 years referring to Scopus queries. As an example in section 4.3 we sketch a completely distributed, agent-based control system for a so-called virtual power plant that was motivated by swarm behavior in nature. In the conclusion we discuss the advantages of such nature-inspired, distributed control methods but also their risks that lead to further research in this domain.

2 Ecological Modeling

Ecological systems are highly complex systems which are characterized by diverse and interacting (social) components. The objective of modeling, in particular of ecological modeling, consists in breaking this complexity down to a (formal) model which reduces the system to some application-specific core elements. The resulting abstract model can be analyzed and helps to gain better insights in the dynamics of the underlying system. With the development of Theoretical Biology, mathematical models were increasingly used: The resulting models are open for qualitative analysis, e.g. graphical representations help to uncover structural dependencies such as cause-effect-relations hierarchies and feedback cycles. Quantitative models, especially differential equations, allow the usage of models for estimating gaps in the collected environmental data or even to extrapolate the future development of the system [Lo25, Fo93]. With the availability of computers, software tools have been developed (Stella, et al.) to support the analysis and allow comfortable simulations. The abstraction level of such system dynamics models is very high: the diversity and heterogeneity of the original system is reduced to a small number of system state variables and parameters and the dynamics described by flows between the state variables. This very abstract modeling is justified in systems with a very high number of individual components as in such systems the aggregated behavioral deviations of individuals can be approximated by the average behavior using averaged parameters. Due to the high degree of abstraction, more detailed views to the system evolved: Individual-oriented models allowed for individual distribution models (IBDM) which split a population by an individual attribute, e.g. age, and model the resulting groups of individuals as separate state variables, but still represent abstracted views to an aggregated system's dynamics which cannot directly be observed in nature. This changed with increased computational power and availability of adequate software tools, e.g. [LS98]: Individual-oriented models (IBCM) go one step further by modeling the individuals of the system and their individual behavior itself, and hence, allow observing interactions between individuals as well as between individuals and environment [HH90, DRH94]. Simulated flocks of birds and fish schools are prominent examples that such models could be used for validating biological theories of emergence phenomena. Additionally, the concept of Cellular Automata [Ho88] allows the micro-scale modeling of spatial processes and the integration of heterogeneous spatial conditions into models.

Common to all these Ecological Modeling approaches is that their objective is to gain insights in the behavior of biological and ecological systems. [HDP88]

3 Nature-Inspired Optimization

The micro-scale approach of individual-oriented modeling allows to model the individual behavior and to observe emergent effects on a macro-scale layer. In combination with the fact that the behavior of biological or ecological systems can be interpreted as an optimization to their environment, this observation has led to new optimization (meta-) heuristics, so-called nature-inspired optimization. Introductory textbooks on this subject are e.g. [Ya10, Br12]. They include several examples of applications as well as pseudo-code for algorithms.

Other than the ecological modeling, nature-inspired heuristics are applied to optimization problems in arbitrary disciplines. Applications range over a broad area of computational problems, e.g. network routing and network design, maximal independent set, minimum spanning tree, space partitioning [NBJ14]. So, there has been a change from applying computer technology for the understanding of natural systems to using patterns of natural behavior for solving computational expensive or intractable optimization tasks [Co96].

In the following, some examples of such nature-inspired optimization techniques are briefly introduced. We differentiate between heuristic approaches with central control and agent-based approaches which produce near-optimal solutions solely by interacting agents.

3.1 Heuristic Approaches

The structure and behavior of Artificial Neural networks (ANN) mimics biological neural networks. They consist of a set of interconnected (artificial) neurons which receive, process and transmit impulses. An artificial neuron is usually only capable of simple computational steps, i.e. the linear combination of inputs and the application of thresholds. The weights and thresholds which are used in the transfer and processing can be trained in order to map a set of inputs (patterns) to outputs [Mi12]. Hence they reflect a mere statistical relation in the input/output data and do not explain any structural aspects. On the global perspective, the realized input/output behavior of a trained neural network can be seen as an emergent process.

Evolutionary algorithms (EA) are one of the best-known nature-inspired optimization meta-heuristics: The evolutionary process which allows species or ecosystems to evolve gradually to an optimal adaption to its environment has inspired different variants of optimization techniques [FP95]. The basic idea which has been implemented in Genetic Algorithms (GA) is to view (non-optimal) solutions of an optimization task as individuals of a population. Chromosomes code the description of the solution. The nature-inspired processes Crossover and Mutation produce candidates for the next generation of solutions by constructing a new combination of two parental chromosomes and by random changes in some attributes (genes) of a chromosome. The candidates which are the fittest related to an arbitrary objective function are chosen for the next generation. So the information about the solution space is distributed over the individuals and coded in their chromosomes, but the evaluation of this information takes place in the centralized selection process.

Particle Swarm Optimization (PSO) [UP11] has been inspired by swarms, herds, and flocks of animals. Similar to GA, a PSO starts with a random population of solutions. The individuals explore the solution space by moving around with individual velocity and direction. After each step, the individuals' solution qualities are evaluated and the position of the global best solution determined. Each individual adapts its direction, and hence its position in the next iteration, by taking its own best as well as the global best solution into account.

In this basic form, the behavior of the particle swarm cannot be viewed as an intelligent swarm [SLW12], as the propagation of the determined global best solution represents a central component. Variants of the PSO modify the propagation of the individual best solution to a local neighborhood and hence can be viewed as intelligent swarm. Furthermore, the knowledge propagation about the known best solution changes to a decentralized process, which opens up the possibility of a completely distributed implementation.

3.2 Agent-Based Methods

In the micro-scale approach of ecological modeling it often can be observed, that the individuals' behavior leads to a global optimum of the overall ecological or biological system. The behavior of fish schools [Re87] illustrates this idea very well: The movement of a fish school completely depends on the simple behavior of the single fishes, their restricted perception of their environment, and their interaction. Each fish's behavior can be reduced to three rules: 1. Avoid collisions 2. Move with the same velocity and direction as other fishes, and 3. Head for fishes which might be joined in the school. Simulations show that these rules can explain the school's movement, which represents an optimal protection strategy. Such systems are called *self-organizing*, as there is no central entity that controls the system's progress, and the global system behavior purely emerges from local interactions. This idea of independent agents with simple behavioral rules and only local knowledge about their environment in combination with other species behavioral patterns has been adopted by agent-based heuristic optimization methods: The behavior of biological ants and bees inspired heuristics for determining short routes by the Ant Colony Optimization (ACO) and for optimizing routing protocols by the Bee Colony Algorithm, resp. [GP10]. In these heuristics the individuals can be viewed as agents in a multi-agent system. Each individual has its own attributes and perception of its local environment and is interacting and communicating with other individuals in order to fulfill its own objectives. Such a system fulfills the definition of swarm intelligence as 'ability to act in a coordinated way without the presence of a coordinator or of an external controller' [SLW12].

4 Challenges in Electrical Power Systems

The purpose of an electrical power system is clearly to provide us with electrical power in the most reliable, economic, environmental friendly, and socially acceptable manner. Obviously these four goals can't be maximized simultaneously, so political and societal weights for these four goals are necessary to design the best possible electrical power system based on the available technology. These weights can be implemented by legal frameworks, market regulations or financial incentives.

Currently, in Germany and in many other countries we undergo a system change originated by weighting up environmental aspects. In combination with emerging new technologies (wind turbines, photovoltaic systems, battery storage) this leads to a major redesign of our power supply system replacing large, nuclear or coal-fired power plants by small renewable energy sources (see e.g. [DII12] for a required scenario of the German power system in the year 2050). In consequence not only the traditional role models and business cases of utility companies are changing, e.g. by private ownership of roof-top solar plants or small co-generation plants, but also accounting systems and control systems of this more and more distributed power supply system are being reconsidered significantly. Additionally the power grid has to be redesigned to adapt to the modified power flow in the grid caused by relocating power plants (see [5014] for the planned development in Germany which is the subject of controversial political discussion).

4.1 Operation and Control Aspects in Power Systems

Many comprehensive introductions into the operation of power systems are available (see e.g. [Me06, Sc12]). Of course in this contribution we have to view things from on a very high level view. In simple terms, apart from the need of matching of supply and demand operation and control of the power system has at least four technical goals to ensure stability:

- The frequency has to be 50Hz at any time (for the continental European power grid) with a maximal deviation of 0.2Hz.
- The voltage band on each voltage level must not be violated (e.g. 210V. . . 250V for the low voltage grid) at any point of the power grid.
- The operating limitations of all active and passive components (e.g. lines, transformers) of the power systems have to be respected.
- The quality of frequency and voltage, e.g. the level of short-term fluctuations and the harmonic-content, has to be optimized.

These are hard constraints to avoid power outages or damage of components. Additionally, from a macro-economic perspective, operation and control of the power system should minimize overall operational cost and also minimize emissions or other type of waste from the operation of nuclear or fossil-fuel power plant. In practice, cost-optimization of power generation refers to single owners or owner communities and is limited by the market conditions. Environmental aspects are integrated into the operation by market rules, e.g. the EEG in Germany [Bu14], that guaranty priority of renewable energy.

So, operation and control of the power supply system includes a highly complex, multi-criteria optimization problem, integrating a huge amount of units (e.g. power plants or controllable loads) with many technical constraints and hard real-time aspects. This complex problem is solved by decomposition into several subproblems. Subproblems can be defined on the one hand by subtasks, e.g. frequency control or local voltage control, and on the other hand by identifying local control circuits, e.g. related to the grid topology, or economical balancing groups.

But with the redesign of our power supply system these operation and control problems becomes even more complex, requiring a 'smart grid'. For example, power generation from photovoltaic and wind power plants is volatile and does not necessarily correlate spatially and temporally to the demand. Moreover, prognosis of power generation from renewable energy comes with some remaining uncertainty. From a technical perspective the system's size also becomes problematic, as the number of power plants to be controlled increases by some orders of magnitude. Furthermore, power plants are now connected to the power grids at all voltage levels – not only at the high voltage and highest voltage level as in the past. To handle these challenges, first approaches aim at developing new decomposition methods – or vice versa aggregation methods for small power plants: virtual power plants (VPPs) [AP97, PRS07] and microgrids [Ha14]. Both attempts combine the operation of small power-plants whereby VPPs mainly act at the market whereas microgrids aim at a local supply-demand matching. But the increasing complexity also motivates research in new optimization and control methods, which will be discussed in the following sections.

4.2 Nature-Inspired Methods

Due to the substantially increased complexity of the power system, optimization heuristics and artificial intelligence methods are an interesting choice for finding new solutions. Thus, research in nature-inspired approaches for power system operation and control gained significant momentum in the past decades. Figure 1 shows the number of publications in this area for the last thirty years, based on a search in the Scopus bibliographic database.[4] Within these publications, most of the research focuses on artificial neural networks as well as evolutionary algorithms, beginning in the late 1980's. Ecologically inspired approaches such as ant/bee/bacterial foraging strategies or firefly/cuckoo search algorithms started appearing in the power systems in the late 1990's (summarized as "other" in the figure). A remarkable milestone was the adoption of particle swarm optimization in the power systems community in the early 2000's, leading to a rapid increase of research in this context.

While these approaches all focus on heuristic optimization, the field of multi-agent systems is more related to coordination and planning problems. Starting already in the 1990's with

[4] http://www.scopus.com, accessed June 3, 2015

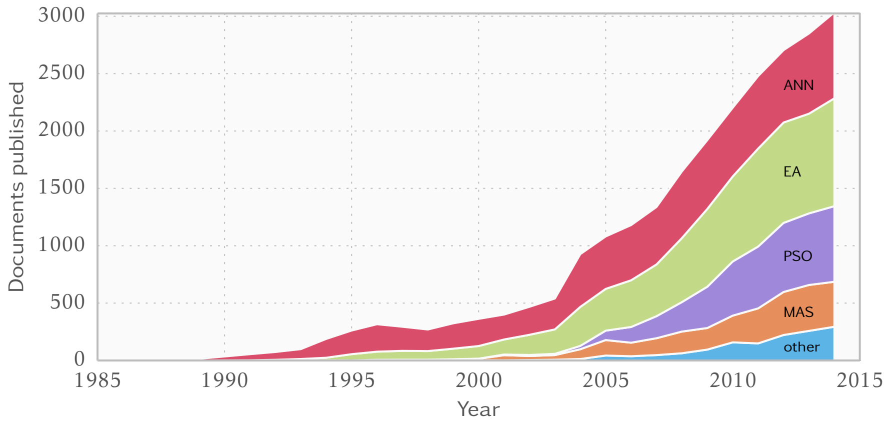

Fig. 1: Scopus query results for research in nature-inspired approaches with application to power systems in the last 30 years, displayed as stacked chart grouped by topic (ANN = artificial neural networks, EA = evolutionary algorithms, PSO = particle swarm optimization, MAS = multi-agent systems, other = ant/bee/bacterial foraging, firefly/cuckoo search algorithms and similar approaches).

only few publications per year in the power systems community, a significant increase of research volume can be seen nowadays in this area, see Fig. 2. This is supported by

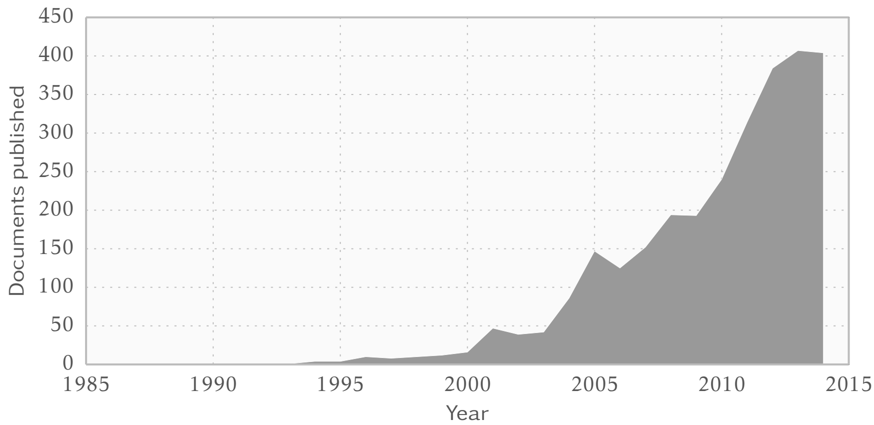

Fig. 2: Scopus query results for research in decentralized nature-inspired approaches with application to power systems in the last 30 years.

the trend towards complex intelligent distributed systems in power systems operation and control, as already outlined in Sect. 4.1. For instance, a research agenda from the point of view of computer science has recently been published in [Ra12], which particularly motivates distributed and agent-based solutions.

4.3 Agent-Based Approaches in Power Systems

As a practical example for an agent-based approach in power systems operation and control, let us consider the balancing of supply and demand. This is necessary for economical reasons and with respect to the first technical goal mentioned in Sect. 4.1. Frequency deviations in the power grid are caused by an imbalance between consumed and produced power. If more power is produced than consumed, the frequency increases and under reverse conditions it decreases. Simplified, this currently results in three tasks of the power supply system:

- Balance between demand and supply has to be achieved first by direct contracts between consumers and producers or at the power market. The latter is enabled by a complex set of products traded in this market [Eu14].
- The operation of controllable power plants (as well as controllable loads such as heat-pumps) has to be planned within groups of plants having jointly sold power products or load profiles in their supply area.
- During execution of the operational plan a system of power reserves has to be available to react instantaneously to unforeseen deviations from forecasts and other events as outage of a power plant. This task is primarily assigned to the transmission grid operator [Eu09].

Let us focus on a the second aspect: the planning of the operation of controllable power plants within a group responsible for delivering a specific power product or load-profile. This planning problem is very well known as the unit-commitment-problem. Established solutions exist for small groups of large controllable plants; for an overview see e.g. [Pa04]. For several years also nature-inspired optimization heuristics are considered to tackle this problem – see e.g. [KBP96] for an early approach. But with the redesign of the power system new challenges arise. For instance, the number of plants to be controlled increases, so highly scalable solutions are required. Further, the members of virtual power plants may change quite often, which calls for easily adaptable optimization methods. Because units in such a virtual power plant can have different owners, each unit also follows its own optimization goals, yielding hybrid multi-objective optimization problems. Finally, owners of power plants might have privacy restrictions regarding information on the operating status of their units. So, optimization might be restricted to limited, abstract state information of units.

Thus, a dynamic agent-based approach seems appropriate for this task. As an example, a suitable approach exists with the concept of Dynamic Virtual Power Plants (DVPP), which is summarized briefly as follows (cf. [Ni12, So15]). In a self-organized way coalitions of plants form with respect to concrete products in an energy market. After delivering a product, a coalition dissolves and the former participating units can then self-determinedly join the formation process of other coalitions for subsequent tradeable energy products. In particular, this comprises the following subprocesses:

1. *DVPP setup:* Plants are aggregated to DVPPs by coalition formation, such that the members of each DVPP agree upon trading a specific power product in the market (e.g. a certain block product in an electricity spot market). Bids for these products are then placed in the market by the respective DVPPs.
2. *Internal scheduling:* After a successful bid, a DVPP is obliged to deliver the power product. For this, the members of the DVPP have to be scheduled within their individually defined degrees of freedom. This is done prior to the actual delivery of the product in a predictive scheduling process which uses mathematical abstractions of the devices' feasible scopes of action.
3. *Continuous scheduling:* To compensate for unforeseen changes or forecast errors, a continuous scheduling is performed during the delivery of the product. Here, the units' schedules are adapted such that product delivery is not endangered.
4. *Payoff division:* Subsequently, the revenues gained from product delivery are distributed among the DVPP members, taking the actual commitment of the units during delivery into account.

In addition to the dynamic nature of this concept, all optimization and control tasks outlined above are realized with fully distributed approaches. Each participating plant is represented by an agent in the system, and the autonomy of the participants is preserved by employing self-organization strategies in the subprocesses. Some results from a preliminary implementation of this concept can be found in [As14].

5 Lessons Learned

In this article, we have sketched how computer science is related to the domain of ecological modeling and to the domain of power system's operation and control. Considered historically, computer science enabled new and much more detailed methods for modeling ecological systems, e.g. by individual-oriented models. This resulted in new insights in the behavior of natural systems. Vice versa, a deeper knowledge of self-organization and adaption in ecological systems inspired new optimization methods as e.g. evolutionary algorithms or methods based on the self-organization of social insects. Although developed somewhat in parallel, individual-oriented modeling in ecology has clearly a strong relationship to multi-agent systems, which are an excellent framework for distributed optimization and distributed control.

As technical systems become more and more complex and distributed, components in these systems become more 'intelligent' by advanced micro-controllers. Besides, communication channels between distributed components become self-evident. So distributed agent-based methods are promising candidates for optimization and control aspects in such technical systems. Electrical power systems are a prime example for this. By replacing a few large fossil-fired or nuclear power supply units by many small wind turbines and photovoltaic systems widely distributed around the power grid, electrical power systems become an even more complex and distributed socio-technical systems.

Self-organized agent-based systems promise in particular high adaptability, fault-tolerance regarding single components, scalability, and – not to forget – privacy of state information of components. But let us reconsider the difficulties that arise with this possible paradigm shift – particularly with regard to the criticality of the infrastructure that has to be controlled. From the viewpoint of ecological and individual-oriented modeling, self-organizing systems usually have been constructed by induction: By analyzing existing systems in nature, interactions among the systems' individuals could be identified and subsequently be adopted to optimization problems. This resulted in widely applicable concrete approaches, such as meta-heuristics.

Regarding the current and upcoming challenges in the optimization and control of complex critical infrastructures however, these generic solutions are often not sufficient any more. Instead, specialized methods and architectures with guaranteed properties are required, where a deductive approach could be more suitable. In such an approach, a system would be constructed with a concrete goal in mind, but based on an abstract yet rigorous methodology to model the system elements and their interactions towards the desired emerging behavior. For instance, in the context of communication networks, an example of such a methodology has been proposed in [PB05]. We believe that this kind of approach will become more important in the future. Although, due to their complex internal dynamics, distributed algorithms and agent-based methods are more demanding with respect to proofs and guarantees on their intended behaviour. Also, agent-systems are in risk to be vulnerable by malicious agents. For an actual adoption in critical infrastructures, these are significant aspects.

In summary, new research challenges arise for design methods for distributed optimization and control methods, especially with a focus on provable guaranteed behavior. In this sense, also the integration of security aspects into agent-based frameworks play a crucial role, see [Ne14]. Finally, high-level standards for complex communication issues in multi-agent systems controlling power system's components will be subject to intensive work.

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